UDC: 004.891.3; 519.216.3 DOI: https://doi.org/10.15407/jai2021.02.78

HYBRID METHOD OF INTELLECTUAL DIAGNOSIS AND FORECASTING OF COMPLEX TECHNICAL SYSTEMS

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Abstract. Modern control and diagnostic systems (CDS) usually determine only the technical condition (TC) at the current time, ie the CDS answers the question: a complex technical system (CTS) should be considered operational or not, and may provide little information on performance CTS even in the near future. Therefore, the existing scenarios of CDS operation do not provide for the assessment of the possibility of gradual failures, ie there is no forecasting of the technical condition.

The processes of parameter degradation and degradation prediction are stochastic processes, the “behavior” of which is influenced by a combination of external and internal factors, so the degradation process can be described as a function that depends on changes in the internal parameters of CTS.

The hybrid method involves the following steps. The first is to determine the set of initial characteristics that characterize the CTS vehicle. The second is the establishment of precautionary tolerances of degradation values of the characteristics that characterize the pre-failure technical condition of the CTS. The third is to determine the rational composition of informative indicators, which maximally determine the "behavior" of the initial characteristics. The fourth — implementation of multiparameter monitoring, fixation of values of the controlled characteristics, formation of an information array of values of characteristics. Fifth — the adoption of a general model of the process of changing the characteristics of the CTS. Sixth — the formation of a real model of the process of changing the characteristics of $Y(t)$ on the basis of an information array of values of characteristics obtained by multi-parameter monitoring. Seventh — forecasting the time of possible occurrence of the pre-failure state of the CTS, which is carried out by extrapolating the obtained real model of the process of changing the characteristics of $Y(t)$. It is proposed to use two types of models: for medium- and long-term forecasting - polynomial models, for short-term forecasting — a linear extrapolation model.

At the final stage, forecast errors are determined for all types of models of degradation of parameters and characteristics. Based on the results of the forecast verification, the models are adjusted.

Keywords: technical condition, parameter degradation, multiparameter monitoring, pre-failure state, polynomial models, extrapolation model.

ГІБРИДНИЙ МЕТОД ІНТЕЛЕКТУАЛЬНОГО ДІАГНОСТУВАННЯ ТА ПРОГНОЗУВАННЯ СТАНУ СКЛАДНИХ ТЕХНІЧНИХ СИСТЕМ

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Анотація. Сучасні системи контролю та діагностування (СКД) визначають, зазвичай, лише технічний стан (ТС) у поточний момент часу, тобто СКД відповідає на питання: складну технічну систему (СТС) слід вважати працездатною чи ні, і при цьому може надавати обмаль відомостей щодо працездатності СТС навіть у найближчому майбутньому. Отже, наявні сценарії роботи СКД не передбачають оцінювання можливості виникнення поступових відмов, тобто немає прогнозування технічного стану.

Процеси деградації параметрів та прогнозування деградації — це стохастичні процеси, на "поведінку" яких впливає сукупність зовнішніх та внутрішніх факторів, тому процес деградації можна описати як функцію, що залежить від зміни внутрішніх параметрів СТС.

Гібридний метод передбачає такі етапи. Перший — визначення набору вихідних характеристик, які характеризують ТС СТС. Другий — встановлення попереджувальних допусків значень деградації характеристик, які характеризують передвідмовний технічний стан СТС. Третій — визначення раціонального складу інформативних показників, які максимально обумовлюють "поведінку" вихідних характеристик. Четвертий — здійснення багатопараметричного моніторингу, фіксація значень контрольованих характеристик, формування інформаційного масиву значень характеристик. П'ятий — прийняття загальної моделі процесу зміни характеристик СТС. Шостий — формування реальної моделі процесу зміни характеристик *Y(t)* на базі інформаційного масиву значень характеристик, здобутого шляхом здійснення багатопараметричного моніторингу. Сьомий — прогнозування моменту часу можливої появи передвідмовного стану СТС, яке здійснюється шляхом екстраполяції здобутої реальної моделі процесу зміни характеристик *Y(t)*. Пропонується використовувати два види моделей: для середньо- та довгострокового прогнозування — поліноміальні моделі, для короткострокового прогнозування — лінійну екстраполяційну модель.

На завершальному етапі здійснюється визначення помилок прогнозу для усіх видів моделей деградації параметрів та характеристик. За результатами верифікації прогнозу здійснюється коригування моделей.

Ключові слова: технічний стан, деградації параметрів, багатопараметричний моніторинг, передвідмовний стан, поліноміальні моделі, екстраполяційна модель.

Modern control and diagnostic (CDS) systems usually determine only the technical condition (TC) of complex technical systems (CTS) at the current time. The existing scenarios of CDS operation do not provide for forecasting the technical condition.

An analysis of recent research and publications on the assessment of the current technical condition and its forecasting shows that almost all known studies are based on the assumption of the stationary process of formation of gradual failures, which is erroneous.

Degradation processes and degradation prediction are stochastic processes. Their "behavior" is influenced, first, by a combination of external and internal factors; secondly, the degradation process can be described as a function that depends on changes in the internal parameters of the CTS. As a result, the use of traditional approaches, which require a very large knowledge base, leads to high computational complexity. Insufficient CDS performance does not cover the full range of possible failure situations during their classification. Learning systems are nonlinear, they are able to classify situations even in conditions of uncertainty, but they do not provide the necessary reliability.

It is proposed to develop a hybrid method of diagnosis, which is based on a combination of approach, which allows to perform also medium- and long-term forecasts, and the approach to perform, including operational forecasting. The hybrid method involves seven steps.

At the final stage, forecast errors are determined for all types of models of degradation of parameters and characteristics. According to the results of the forecast verification (provided that the errors exceed the limit values that are set in advance), the adjustment of, first, the models obtained with the help of both MGUA and BMLE is carried out; sec-

ondly, monitoring parameters, in particular time quantization intervals.

Statement of the problem in general

Assessment of the state of complex technical systems (CTS) is usually carried out using a monitoring and diagnostic system (MDS). However, modern CDS usually determine only the technical condition (TC) at the current time, CDS answers the question: CTS should be considered operational or not, and may provide little information about the operability of CTS even in the near future. Therefore, the existing scenarios of CDS do not provide for the assessment of the possibility of failures, which are called gradual, there is no forecasting of the technical condition [1] – [4], which allows to predict the failure of CTS and timely initiate appropriate preventive actions to maintain serviceability of CTS.

Thus, the issues of correct formulation of the procedure for assessing and forecasting the performance of STS with the use of multiparameter monitoring, the formation of a list of indicators by which it becomes possible to carry out current assessment, as well as accurate and reliable forecasting, should be considered relevant.

Analysis of recent research and publications. An analysis of recent research and publications on the assessment of the current technical condition and its forecasting [1] – [6] shows that much attention has been paid to determining the current technical condition of technical facilities, but much less research has been carried out related to TC forecasting. Moreover, almost all known studies are based on the assumption of the stationary process of formation of gradual failures, which is erroneous and, accordingly, a significant disadvantage of such methodological approaches.

Another area of research is the use of accumulated information about the values of current parameters that determine the TC, which becomes possible due to almost constant multi-parameter monitoring. However, as a rule, forecasting of the TC is either not carried out, reducing the study to the construction of the current TS signature and its validation, or obtain a forecast with large errors [7] – [9].

In addition, it should be noted that the approach, which is based on the use of accumulated information about the values of current parameters, requires significant computing power - especially the speed of information processing and the establishment of primitive causal relationships. This is due to the fact that the application to implement the model of degradation of the TC, for example, the method of group argumentation requires, first, a significant sample; secondly, such a polynomial model is not capable of sensitivity, ie does not take into account the "rate" of changes in parameter values and, accordingly, does not allow regulation of the duration of observation intervals (according to, for example, Kotelnikov's theorem) and prediction. in determining and forecasting the TC, and its size. In addition, polynomial models, which are created by the method of group argumentation requires, do not have such a quality as emergence, ie the model is not able to take into account the sudden factors that affect the controlled indicator. As a result, it can be concluded that the use of method of group argumentation requires (and other similar methods) may be appropriate, primarily to create a medium- and long-term forecast [3].

It is worth noting that attempts have already been made to determine the technical condition of the CTS and predict it. An example is the work [10], which proposes to use the Berg method and Shi models based on Bayesian networks to solve problems of diagnosing and forecasting of complex technical systems. But most researchers still believe that the most convenient device for solving problems of diagnosis and prediction are artificial neural networks [11] – [15].

Thus, it can be reasonably concluded that the methodological approaches currently used to determine the TS are not sufficiently consistent with the solution of the problem of forecasting the technical condition.

The purpose of the article

The purpose of the article is to present a hybrid method of intelligent diagnosis and prediction of complex technical systems using multi-parameter monitoring, as well as correction of monitoring parameters during observations.

Presentation of the main research material.

First of all, it should be determined that the processes of degradation and, accordingly, the prediction of degradation, which are the subject of this article, are stochastic processes, the "behavior" of which is first influenced by a combination of external and internal factors; secondly, the degradation process can be described as a function that depends on changes in the internal parameters of the CTS. As a result, the use of traditional approaches, which require a very large knowledge base, leads to high computational complexity. Insufficient CDS performance does not cover the full range of possible failure situations during their classification. Learning systems are nonlinear, they are able to classify situations even in conditions of uncertainty, but they do not provide the necessary reliability [9]. Thus, given the fact that none of the above approaches to the diagnosis of CTS can be used alone, automatic diagnosis of the TC based on observations obtained during monitoring requires the development of a specific hybrid method. It is proposed to develop a method of diagnosis, which is based on a combination of approach, which allows to perform also medium- and long-term forecasts, and the approach to perform, including operational forecasting.

The hybrid method involves the following steps [16] – [18]:

a) determination of a set of initial characteristics $\{Y_1, Y_2, \ldots, Y_n\}$, which characterize the TC of CTS with a predetermined probability. Output characteristics can be parameters of output signals (for example, power, frequency, pulse duration, pulse amplitude, etc.) or some system parameters (amplitude and phase characteristics, bandwidth, sensitivity, etc.);

b) establishment of precautionary tolerances of degradation values of characteristics $\{Y_1, Y_2, \ldots, Y_n\}$, which characterize the pre-failure technical condition of CTS. Advance tolerance is understood as the value of the characteristics between the limit and pre-failure levels. The output of the value of the characteristic for the limit level means failure, and the achievement of the pre-failure level — the need for maintenance or replacement of elements of the CTS, ie inconsistencies of the first or second type;

c) determination of the rational composition of informative indicators that determine the maximum "behavior" of the initial characteristics:

$$\{Y_i\}=f\{X_n\},$$

where $X = \left(x_1, x_2, \ldots, x_n\right)$ — "input" parameters;

d) implementation of multiparameter monitoring, fixation of values of controlled characteristics, formation of an information array of values of characteristics, which should be presented in the form of a matrix:

$$Y_{nm}=\begin{pmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{pmatrix},$$

where:

m — is the total number of controlled characteristics of the CTS;

n — is the number of measurements of each characteristic on the monitoring interval T.

In the resulting matrix, the number of columns increases as monitoring. Each column represents a point in the Euclidean configuration space, which should be denoted by $\{i = 1, \ldots, n\}$, and each row is a sequence of $\{j = 1, \ldots, m\}$ measurements of the values of the controlled characteristics;

d) adoption of a general model of the process of changing the characteristics of CTS — function $Y(t)=\{Y_i(t)\}^n_{i=1}$,, and it should be borne in mind that the peculiarity of the process of changing the characteristics of $Y(t)$ is its pronounced non-stationary throughout the monitoring interval, due to the presence in $Y(t)$ of an irreversible component that characterizes the aging or wear process;

e) formation of a real model of the process of changing the characteristics of $Y(t)$ on the basis of an information array of values of characteristics obtained by multi-parameter monitoring. As a rule, the most adequate models are statistical, based on time series;

f) forecasting the time of possible occurrence of the pre-failure state of the CTS, which is carried out by extrapolating the ob-

tained real model of the process of changing the characteristics of *Y (t)*.

The procedure for forecasting the technical condition is to form a model of some a posteriori (conditional on the observed implementation of *Y (t)*) random process based on monitoring data and a priori information and further evaluate its characteristics. The formed model of a posteriori process characterizes individual properties of CTS. The result of the forecast, at the same time, gives an assessment of the condition, which is valid for the observed CTS.

It is proposed to use two types of models:

– for medium- and long-term forecasting — polynomial models, which are obtained using the well-known MSUA [19]. But it should be noted that as basic models are widely used not only polynomials, but also nonlinear, probabilistic functions or clustering [20];

– for short-term forecasting — a linear extrapolation model, which is obtained using the method of multidimensional linear extrapolation (MDLE), the use of which allows to perform the task of forecasting the technical condition of the CTS.

The essence of the MDLE method is quite traditional finding the values of indicators of a system at a point outside the observation segment, their values within this segment. The problem of creating an approximation model (A-Model) is a problem of spatial interpolation and extrapolation, which is described by such terms.

Let there be a finite set of experiments-points in the space of experiments in the *g*-th period of time T, where some indicators of the system are defined. The task is to estimate the value of the vector of indicators of the system in a new experiment that is not contained in the specified set at the q-th time t under the condition: $t_q \notin T$.

In general, the problem is formulated as follows. It is necessary to find the transformation operator F from the equation:

$$Y = F(X),$$

where $X = \{X_1, X_2, \ldots, X_S, t\}$ is the vector of input parameters that determines the coordinates of the experience point in the subspace of parameters and on the time axis, which is the Euclidean space of dimension S;

S — the number of parameters on which the characteristics of the system depend;

$Y = \{Y_1, Y_2, \ldots, Y_m, t\}$ is a characteristic vector that determines the coordinates of the experience point in the characteristics subspace, which is a Euclidean space of dimension m;

m is the number of system characteristics;

F is a transformation operator that maps a subspace of parameters to a subspace of characteristics.

The problem is to recover the vector F by some set of vectors {X}, for which the values of the vectors {Y} are known. That is, when observing a real system, a training sample is obtained — a number of K points for which the vector Y is assigned to each vector X at time t.

The use of the MDLE method assumes that the process of changing the values of parameters and characteristics is piecewise linear throughout the direct use of CTS. It follows from this assumption:

Subspaces of parameters and characteristics are linear. Thus, the equations for the elements of these subspaces can be written as follows:

$$\{X\} = X_1 + \sum_{i=1}^{k-1} \lambda_i (X_{i+1} - X_1),$$

$$\{Y\} = Y_1 + \sum_{i=1}^{k-1} \mu_i (Y_{i+1} - Y_1),$$

where $X_i,\ i = \overline{1,k}$ — vectors in the subspace of parameters, each of which corresponds to a vector in the subspace of characteristics $Y_i,\ i = \overline{1,k}$ on the basis of k measurements;

$\lambda_i,\ \mu_i,\ i = \overline{1,S}\,\overline{1,k}$ — coefficients of the corresponding vector linear subspaces.

2. The mapping of the subspace of parameters to the subspace of characteristics is linear — $\lambda_i = \mu_i$.

Thus, the task of forecasting is reduced to the following stages: sampling; calculation of the predicted value of the characteristic Y *; determination of forecast errors.

Based on the results of observing the change in the parameters X and the

characteristics Y, measured at time intervals τ, a sample of *k (k≥S+1)* implementations of the S-dimensional vector is formed. The interval τ of fixing the values of X_i and Y_i is chosen so that if the forecast states that the value of the characteristic Y* exceeds the tolerance α, β, the advance τ would allow to take organizational and technical measures to prevent failure.

From k measuring points k'(k' <S + 1) of implementations which satisfy functions $\Phi\left(\overline{X_i}, X\right)$ which is a criterion of proximity is chosen:

$$\Phi(\overline{X_i}, X)=\sum_{i=1}^{S} (\overline{X_i} - X_i)^2,\ \Phi(\overline{X_i}, X)\to min,$$

where $\overline{X_i}$ is the value of the i-th parameter that lies outside the observation segment.

By k 'measurement points, the function F is restored.

The next step is to calculate the linearity coefficients λ. To do this, a system of equations:

$$\lambda_1\sum_{i=1}^{S}h_{i1}^2+\lambda_2\sum_{i=1}^{S}h_{i1}h_{i2}+\ldots+\lambda_{k'-1}\sum_{i=1}^{S}h_{i1}h_{ik'-1}=\sum_{i=1}^{S}h_{i1}-U_i$$

$$\lambda_1\sum_{i=1}^{S}h_{i1}h_{i2}+\lambda_2\sum_{i=1}^{S}h_{i2}^2+\ldots+\lambda_{k'-1}\sum_{i=1}^{S}h_{i2}h_{ik'-1}=\sum_{i=1}^{S}h_{i2}-U_i$$

$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$

$$\lambda_1\sum_{i=1}^{S}h_{i1}h_{ik'-1}+\lambda_2\sum_{i=1}^{S}h_{i2}^2h_{ik'-1}+\ldots+\lambda_{k'-1}\sum_{i=1}^{S}h_{i2}h_{ik'-1}=\sum_{i=1}^{S}h_{ik'-1}-U_i,$$

where

$$U_i=\overline{X_i} - X_i,\ i=\overline{1,S};$$

$$h_{ij}=X_{j+1i} - X_{1i}.$$

The system is written as an equation using a matrix form:

$$H^T H \lambda = H^T U, \qquad (1)$$

$$\text{де } H=\begin{pmatrix} h_{11}h_{12}\ldots h_{1k'-1} \\ h_{21}h_{22}\ldots h_{2k'-1} \\ \cdots\cdots\cdots\cdots \\ h_{S1}h_{S2}\ldots h_{Sk'-1} \end{pmatrix};\ \lambda=\begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \ldots \\ \lambda_{k'-1} \end{pmatrix};$$

$$U=\begin{pmatrix} U_1 \\ U_2 \\ \ldots \\ U_S \end{pmatrix}.$$

The coefficient λ is from equation (1):

$$\lambda = H^T \bullet U\ (H^T \bullet H)^{-1}.$$

The predicted value of the characteristic Y * is determined from the expression:

$$Y^* = Y_1 + \sum_{i=1}^{k'-1}\mu_i\left(Y_{i+1} - Y_1\right),$$

where $\mu_i= \lambda_i,\ i=\overline{1,k}$ according to the previously accepted assumption.

At the final stage, forecast errors are determined for all types of models of degradation of parameters and characteristics. According to the results of forecast verification (provided that the errors exceed the limit values (φ, ω), which are set in advance), the adjustment is obtained, first, the models obtained using both MSUA and BMLE; secondly, monitoring parameters, in particular time quantization intervals Δt_i (Fig. 1).

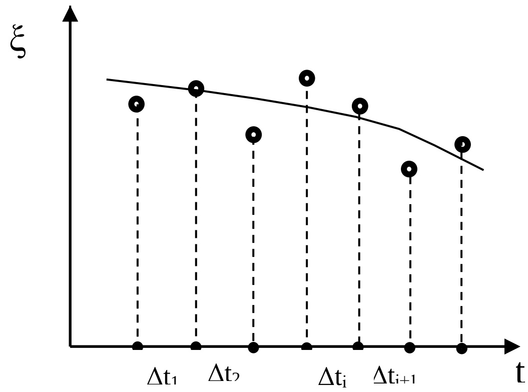

Fig. 1. The procedure for determining the discreteness of fixing parameter values

To solve this problem, we hypothesize that the process of changing the values of the observed parameter ξ(t) is stationary. In this case, the value of the discreteness of the time of fixing the values of the process of changing the parameters of the CTS is determined based on the expected model of the process of changing the values of the parameter ξ(t) (usually the time series is selected as a model of such a process) [21]. To form a model, according to the results of monitoring the process of changes in the values of the parameter ξ(t), an approximation function is constructed. Obtaining such a function in analytical form makes it possible to calculate it, after which, taking into account the value of the upper limit frequency of the spectrum of the approximation function, according to Kotelnikov's

theorem, the value of the time discreteness of fixing the values of parameters Δt is calculated. It should be emphasized that when the condition of stationarity (quasi-stationarity) of the process on the observation interval of the value Δt=const.

However, the real processes of changing the values of the parameters of the CTS are often not stationary and in this case may require correction of both the model and, accordingly, the value of the discreteness of the fixation time. To do this, at each fixation point t_i ($t_i \in T$, T is the monitoring interval of the parameter $\xi(t)$), the values of the parameter $\xi(t)$ are calculated $\frac{d\xi}{dt}$. If $\left|\frac{d\xi}{dt}\right|$=0, then the model of the process of changing the values of the controlled parameter is not adjusted, and, accordingly, on the observation interval the value Δt = const. If the condition is fulfilled after the next control step, which is performed at the point tj, then the spectrum of the function $\left|\frac{d\xi}{dt}\right| \square\ 0$, its upper frequency is calculated again and, accordingly, the discreteness of the observation interval $\Delta t_i + 1$ is calculated. Thus, the discreteness of the observation is adjusted.

After adjusting the model in the next measurement, the stationary of the process of changing the values of the parameter $\xi(t)$ is checked — the second derivative of the function — the model of the process of changing the values of the parameters is calculated $\xi''(t)$. If the condition is met $\xi''(t)=0$, the model is not adjusted ξ 0, if it is necessary to reform the model of the process of changing the values of $\xi(t)$ [22].

A simplified block diagram of the proposed methodological approach to assessing and forecasting the technical condition of the CTS is presented in Fig. 2.

Conclusion

It is proposed a hybrid method of intelligent diagnostics and forecasting of the condition of complex technical systems with the use of multiparameter monitoring, as well as correction of monitoring parameters during observations of the technical condition of complex technical systems (CTS). The method also provides for the possibility of adjusting the type or model of functions that describe the processes of changing the values of parameters and characteristics of the technical condition. Adjustment is possible and appropriate in case of non-stationary process observed.

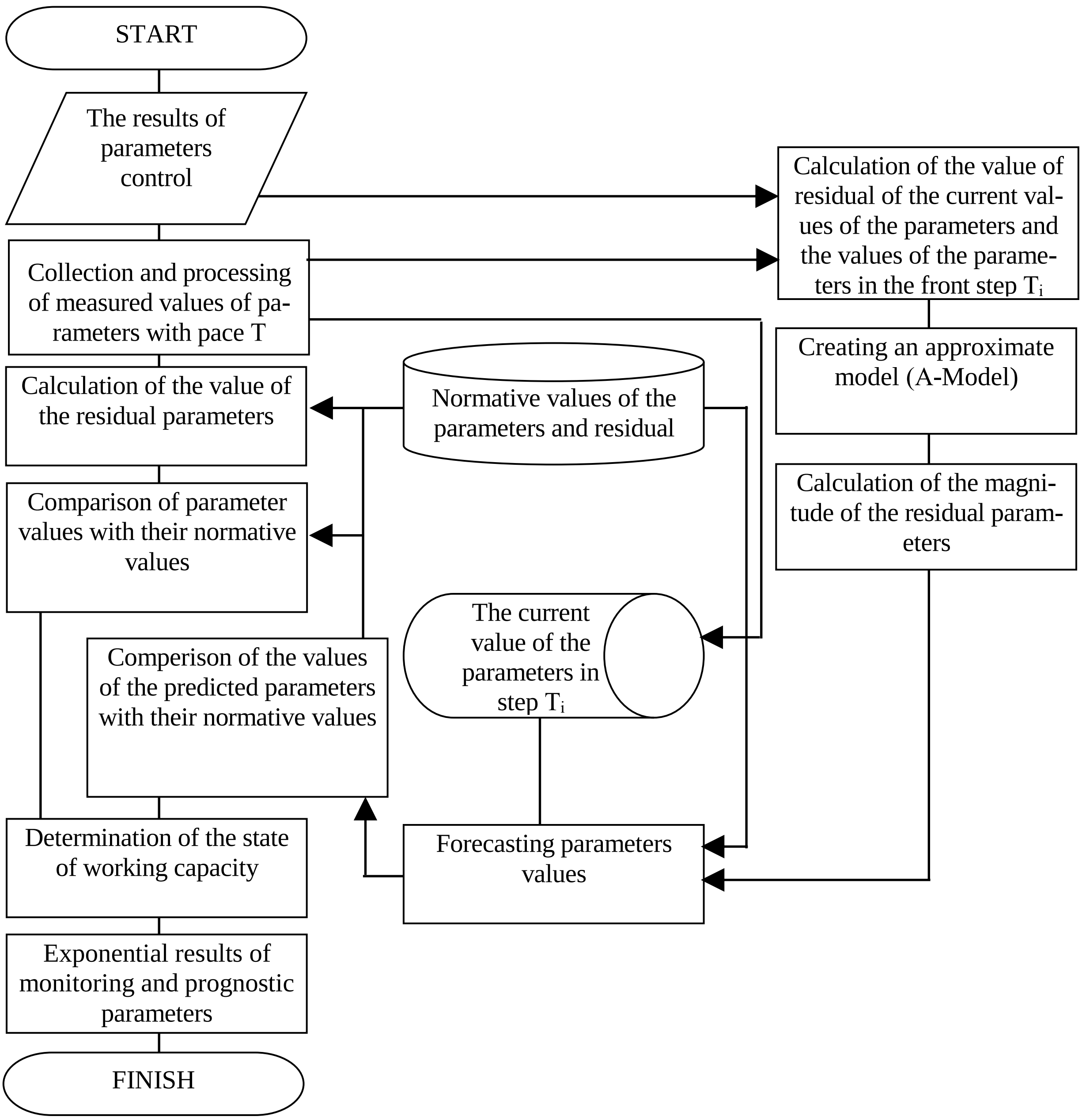

Fig. 2. Simplified block diagram of the algorithm for diagnosing and forecasting the technical condition of a complex technical system

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Received 26.08.21
Accepted 02.10.21